A Comparison of ANFIS and ANN for the prediction of Peak Ground Acceleration in Indian Himalayan Region

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Abstract. Peak ground acceleration (PGA) plays an important role in assessing effects of earthquakes on the built environment, persons, and the natural environment. It is a basic parameter of seismic wave motion based on which earthquake resistant building design and construction are made. The level of damage is, among other factors, directly proportional to the severity of the ground acceleration, and it is important information for disaster-risk prevention and mitigation programs. In this study, a hybrid intelligent system called ANFIS (the adaptive neuro fuzzy inference system) is proposed for predicting Peak Ground Acceleration (PGA). Artificial neural network and Fuzzy logic provide attractive ways to capture nonlinearities present in a complex system. Neuro-Fuzzy modelling, which is a newly emerging versatile area, is a judicious integration of merits of above mentioned two approaches. In ANFIS, both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic are combined in order to give enhanced prediction capabilities, as compared to using a single methodology alone. The input variables in the developed ANFIS model are the earthquake magnitude, epi-central distance, focal depth, and site conditions, and the output is the PGA values. Results of ANFIS model are compared with earlier results based on artificial neural network (ANN) model. It has been observed that ANN model performs better for PGA prediction in comparison to ANFIS model.

Keywords: Peak Ground Acceleration (PGA), Adaptive Neuro-Fuzzy Inference System (ANFIS), ANN, Root-Mean-Square error, Modelling.

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1 Introduction

In the estimate of seismic risk, the determination of ground motion parameters like spectral characteristics, peak ground displacement and peak ground acceleration is very important for a quantitative assessment of the problem. The knowledge of these parameters provides the basis for a classification of the territory and identifies the areas for which great damage in case of strong earthquakes is expected. Peak Ground Acceleration (PGA) is the most commonly used parameter for seismic hazard studies. It is mostly estimated by the attenuation relationships developed for the region. Accordingly, a number of studies have been done to obtain the attenuation relations for PGA for various regions of the world by different researchers ([3, 15] for China region, [17] for Italian region, [1]). Based on the Indian strong motion data an attenuation relationship for peak horizontal acceleration has been given by [6] for Koyna region and a relationship for Himalaya region has been developed by [19, 20, 13]. Most of these studies are based on regression or multiple regression analysis of large data sets of strong motion acceleration records. The PGA at a site is affected by many factors such as the size of earthquake (magnitude), distance of the site from the source, site conditions, fault type and tectonic environment. Modern artificial intelligence methods such as neuro-fuzzy systems can be used for the prediction of PGA. These methods provide fast, reliable and low-cost solutions. Another advantage of these methods is that they can handle dynamic, non-linear and noisy data, especially when the underlying physical relations are very complex and not fully understood. The purpose of this study is to investigate the applicability of ANFIS in prediction of PGA using the strong motion data available for the Himalayan Region, as a soft computing technique to remove uncertainties in attenuation relations.

2 Data Used

The data used in this study pertains to the SMA data [4, 5] and the focal parameters for all Indian events [7]. There are eight earthquakes (Table 1) contributing data for the present study, one of which has been recorded by Kangra array, two by Uttaranchal array and five by Shillong array.

These data are normalized according to the following expression given in Eq. (1). There are two advantages to normalize data before processing in ANFIS for prediction. One advantage is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges, and the other advantage is to avoid numerical difficulties during the calculation. It is recommended to linearly scale each attribute to the range [-1, +1] or [0, 1]. In the modeling process, all data values were scaled to the range between 0 and 1 as follow:

$$X_n = \frac{X_i - X_{min}}{X_{max} - X_{min}} \qquad \mathbf{i = 1, 2, \ldots, n} \tag{1}$$

where, X_n is the normalized value, X_i is the actual value and X_{max} and X_{min} are the maximum and minimum measurement values within the whole data set. Such normalization procedures render the data into dimensionless form. Furthermore, normalization also removes the arbitrary effects of similarity between objects and to increase rate answer data to input signal.

Total 109 datasets are used for the study comprising parameters such as magnitude of the earthquake, epicentral distance, focal depth and site condition. The 70% of the simulated sample in a random order formed the training data set while the remaining 15% each of simulated sample in a random order were used as network validation and testing data set.

Table 1: Locations of the earthquake events under study

Earthquake	**Magnitude (m_b)**	**Epicenter Latitude**	**Epicenter Longitude**	**Focal depth (km)**	**No. of stations**
Dharmsala (26 April 1986)	5.5	32.18°N	76.28°E	7	9
Shillong (10 Sept. 1986)	5.5	25.42°N	92.08°E	28	12
N.E. (18 May 1987)	5.7	25.27°N	94.20°E	50	14
N.E. (6 Feb. 1988)	5.8	24.64°N	91.51°E	15	18
N.E. (6 Aug. 1988)	5.8	25.14°N	95.12°E	91	33
Uttarkashi (20 Oct. 1991)	6.6	30.78°N	78.78°E	12	13
Chamoli (29 Mar. 1999)	6.8	30.41°N	79.42°E	21	10

3 Methodology

The ability of a neural network (NN) is combined with fuzzy logic (FL) reasoning in order to form a hybrid intelligent system called ANFIS (adaptive neuro-fuzzy inference system). The goal of ANFIS is to find a model or mapping that will correctly associate the inputs (initial values) with the target (predicted values). The fuzzy inference system (FIS) is a knowledge representation where each fuzzy rule describes a local behavior of the system. The network structure that implements FIS and employs hybrid-learning rules to train is called ANFIS [12].

3.1 ANFIS Approach

ANFIS is a new inference system [8,9], in which a universal approximator is introduced to represent highly nonlinear functions. This model, first explored systematically by [21], has found numerous practical applications in control [16, 18], prediction and inference [10, 11]. An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule is the well-known back-propagation method, which seeks to minimize some measure of error, usually sum of squared differences between network's outputs and desired outputs. Generally, the model performance is checked by the means of distinct test data, and relatively good fitting is expected in the testing phase. Considering a first-order Takagi, Sugeno and Kang (TSK) fuzzy inference system, a fuzzy model contains two rules[18]:

If x is A_1 and y is B_1, then $f = p_1 x + q_1 y + r_1$ (rule 1)

If x is A_2 and y is B_2, then $f = p_2 x + q_2 y + r_2$ (rule 2)

Where A_1, A_2, B_1, B_2 are the membership functions for input x and y; p_1, q_1, r_1, p_2, q_2, r_2 are the parameters of output function.

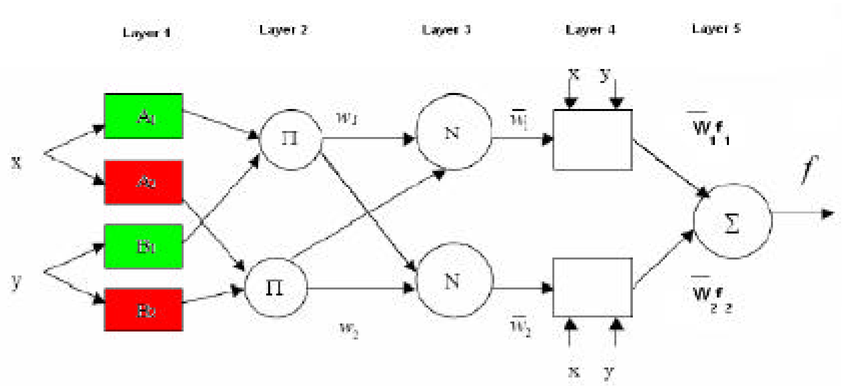

Fig.1. Fuzzy reasoning for the ANFIS model

The fuzzy reasoning for the model is illustrated in Fig.1. A fuzzy inference system consists of five layers and each layer is formed by several nodes and node functions. There are two types of nodes: adaptive nodes and fixed nodes. Adaptive nodes are marked by squares that represent the parameter sets and can be adjustable in these nodes. Fixed nodes are marked by circles, and the parameter sets are fixed in the system.

Layer 1: The entire node *i* in this layer are the adaptive nodes

$$O_{1,i} = \mu A_i(x)$$
$$O_{1,i} = \mu B_i(y) \qquad \textbf{for } i = 1, 2$$

where, x and y are the input nodes; A and B are the linguistic labels; $\mu A_i(x)$ and $\mu B_i(y)$ are the membership functions.

Layer 2: Every node of this layer is a fixed node. It is labeled as p and marked by a circle. The output of each node is the product of all the incoming signals.

$$\mathbf{O_{2,i} = \omega_i = \mu A_i(y).\mu B_i(y)} \qquad \textbf{with i = 1, 2}$$

The output node **?** $_i$ presents the firing strength of a rule.

Layer 3: Every node of this layer is a fixed node marked by a circle and labelled as N. The outputs of this layer are called as normalized firing strengths. The output is calculated by the ratio of the *i* th node firing strength over the sum of all rules' firing strength.

$$\mathbf{O_{3,i} = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \text{ with } i = 1, 2}$$

Layer 4: Every node i in this layer is a square node with a node function.

$$\mathbf{O_{4,i} = \overline{\omega_i}.f_i = \overline{\omega_i}.(p_i x + q_i y + r_i) \text{with } i = 1, 2}$$

Where, $\overline{\boldsymbol{\omega_i}}$ is the output of layer 3, and is the parameter set. Parameters in this layer will be referred as ' consequent parameters' .

Layer 5: The single node in this layer is a circle node labeled ? that computes the `overall output' as the summation of all incoming signals, i.e.,

$$\mathbf{O_{5,i} = overall\ output = \sum_i \omega_i.f_i = \frac{\sum_i \omega_i.f_i}{\sum_i \omega_i}}$$

This adaptive network is equivalent to Sugeno Fuzzy Model. In order to develop a formula to find the values of non- linear premises parameters and linear consequences parameters {$\mathbf{p_i}$, $\mathbf{q_i}$, $\mathbf{r_i}$ }, various Hybrid Learning Algorithms are used.

If we fix Premises parameter then f, overall output can be expressed as linear combination of consequent parameter as:

$$\begin{aligned}\mathbf{f} &= \textstyle\sum_i \bar{\omega}_i \mathbf{f}_i \\ &= \textstyle\sum_i \bar{\omega}_i (\mathbf{p}_i \mathbf{x} + \mathbf{q}_i \mathbf{y} + \mathbf{r}_i) \\ &= \textstyle\sum_i (\bar{\omega} \mathbf{p}_i)\mathbf{x} + (\bar{\omega} \mathbf{q}_i)\mathbf{y} + (\overline{\omega})\mathbf{r}_i\end{aligned}$$

which is linear in the consequent parameters $\mathbf{p_i}$, $\mathbf{q_i}$, $\mathbf{r_i}$

3.2 ANFIS Model Setup

Fuzzy Logic Toolbox available in MATLAB is used for training ANFIS. A computer program was written in MATLAB and the same is appended as Annexure-I. According to the ANFIS tools and guidelines, there are two main things to be done in ANFIS model setup as follows:

*I. **Sugeno ANFIS network setup***

This process is conducted with a command ‘ genfis1’ with numMF is 2 and mftype is ‘ gbellmf’ . The architecture of the above described ANFIS Model is shown in Figure 2 which uses hybrid learning. The generated membership functions are able to show the interactions and relationship between the experimental levels. Figure 3 shows the fine curves of the trained model with smooth curve interaction for each parameter indicating the best fit of the developed model.

*II. **ANFIS Training processes***

The training process proceeded with a command ‘ anfis’ with back propagation method and 200 epochs. Once the network is trained, the test data can be processed with same training parameters for the prediction. Figure 4 displays the level of accuracy in terms of error achieved

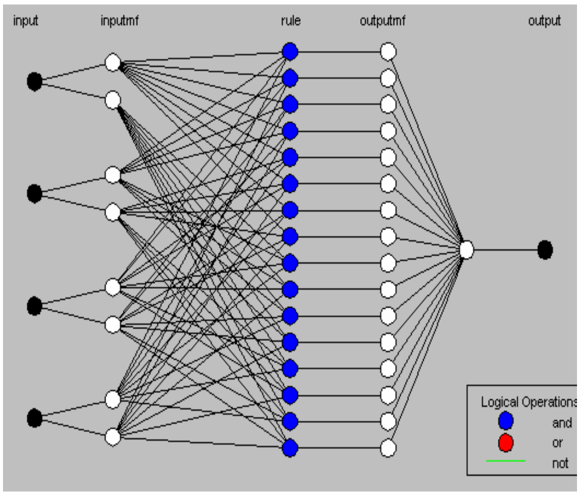

Fig.2. Architecture of Sugeno ANFIS Model

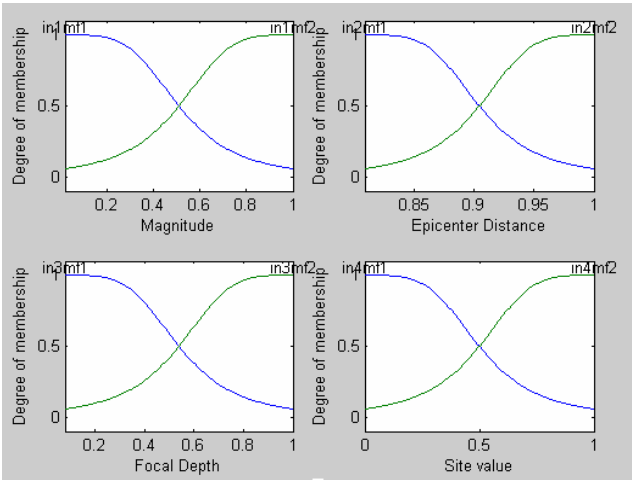

Fig.3. Membership function of each parameter for the tested model

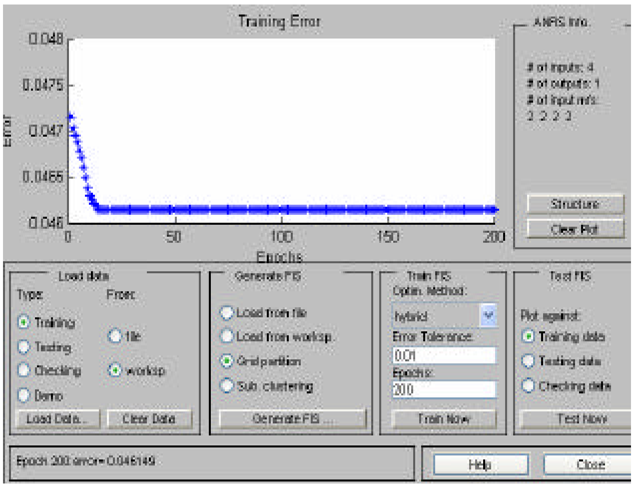

Fig.4. Error change during training

4 Results and Discussion

An ANFIS model is developed in this study for PGA prediction using the input variables magnitude, source-to-site distance, depth and the site conditions. After experimenting with different learning algorithms at different epochs, best correlations are observed through hybrid learning algorithm at 200 epochs. The adequacy of the developed ANFIS was evaluated by considering the coefficient of correlation (R^2) and the root mean squared error (RMSE). The observed correlation coefficient for this study is 0.6807 and the RMSE is 0.04688 as shown in the Figure 5.

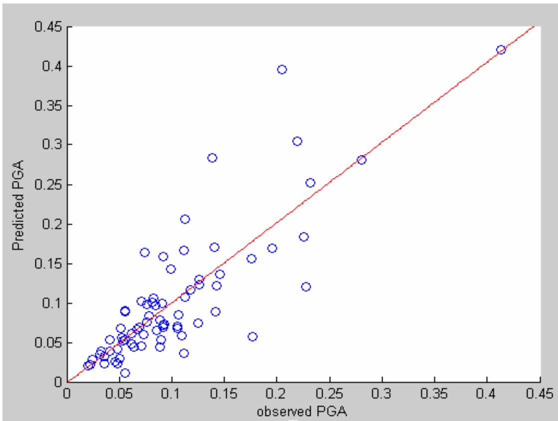

Fig.5. Performance of ANFIS model in the prediction of PGA

The results obtained through ANFIS model are compared with the earlier ANN approach [14] with same data set. In ANN approach, a Feed-forward back- propagation (FFBP) training algorithm was used. Neural networks with different architectures were trained, validated and tested with the same set of data. Due to the use of logarithmic sigmoid function as activation function in this approach, inputs were normalized to [0 1] before being processed through ANN. The neural network with 4×4×1 architecture produced better results in comparison to other networks. As observed in case of ANN approach, the correlation coefficient (R^2) was 0.85 and RMSE was 0.039. RMSE and R^2 plots are shown in Figure 6 along with the best fit.

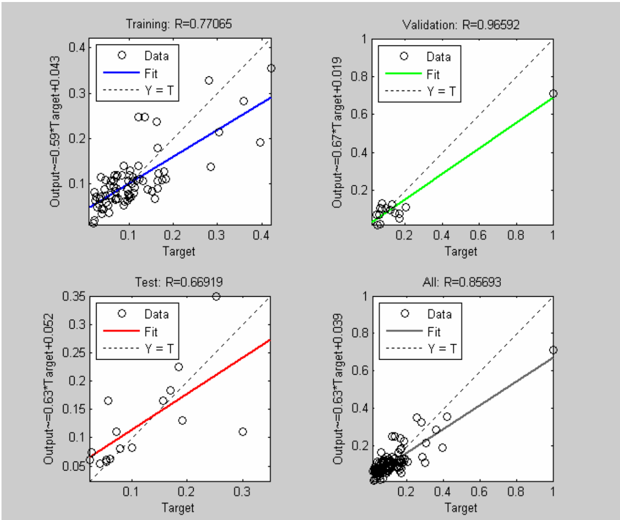

Fig.6. Performance of ANN model in the prediction of PGA

5 Conclusions

In this study, the abilities of ANFIS models in estimating Peak Ground Acceleration (PGA) were evaluated. Results of ANFIS model are compared with earlier results based on artificial neural network (ANN) model. It is observed that the ANN model performs better than the ANFIS model in this case. The main advantages of ANNs are their flexibility and ability to model nonlinear relationships. Mathematically, an ANN may be treated as a universal approximator [2]. This technique has already become a prospective research area with great potential because of the ease of application and simple formulation. Moreover, the ANFIS models combine the transparent and linguistic representation of a fuzzy system with the learning ability of the ANN. Therefore, they can be trained to perform an input/output mapping, just as with an ANN, but with the additional benefit of being able to provide the set of rules on which the model is based.

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Annexure-I

```
load pdata.mat
s1=pdata;
Input=s1 (1:72, 1:4);
Output=s1 (1:72, 5);
input_chk=s1 (73:109, 1:4);
out_chk=s1 (73:109, 5);
trndata=[input output];
chkdata=[input_chk out_chk];
stepsize = 0.1;
FIS = genfis1 (trndata);
[fismat1, error1, ss, fismat2, error2] = anfis (trndata, FIS, [200 0.01 0.1], [1 1 1],
chkdata);
figure (2)
subplot(2,2,1)
plotmf(FIS, 'input', 1)
subplot(2,2,2)
plotmf(FIS, 'input', 2)
subplot(2,2,3)
plotmf(FIS, 'input', 3)
subplot(2,2,4)
plotmf(FIS, 'input', 4)
figure(3)
subplot(2,2,1)
plotmf(fismat2, 'input', 1)
subplot(2,2,2)
plotmf(fismat2, 'input', 2)
subplot(2,2,3)
plotmf(fismat2, 'input', 3)
subplot(2,2,4)
plotmf(fismat2, 'input', 4)
figure(4)
plot([error1 error2]);
hold on; plot([error1 error2], 'o');
xlabel('Epochs');
ylabel('RMSE (Root Mean Squared Error)');
title('Error Curves');
result=evalfis(input, fismat1);
```

```
result1=evalfis(input_chk,fismat1);
error =result-output ;
rmsdata= mse(error,result);
rmse =sqrt(rmsdata);
```